Relative Benefits of Potential Autonomy Technology Investments

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Abstract

JPL is considering the development and launch of a roving long-range, long-duration science laboratory to Mars that will be a major leap in the in-situ exploration of Mars. This paper focuses on methods to determine relative benefits of autonomy technology development investments for accomplishing this mission's goals.

We developed a framework that looks at both cost and risk early in the design process in order to determine the investment strategy in new technology development that will lead to the lowest risk mission possible which enables desired science return within a given budget. The work was performed under NASA's Engineering for Complex Systems (ECS) program.

1. Introduction

A long-duration science mission to Mars has time constraints. Communication with earth is limited to only two intervals a Martian day, assuming the current space infrastructure. A rover dependent on communication with Earth for detailed decision-making will have reduced productivity over a more autonomous rover. Risk models are presented to estimate the probability that time is sufficient to meet mission goals for several potential levels of autonomy capability.

The analysis focuses on currently deployed rover autonomy technologies for which extensive terrestrial experiment data is readily available and where the field data has been collected in the context of system performance evaluation based on integrated field-testing for Mars rovers. The performance failure rate data is from the JPL technology rover FIDO over the course of four years of field trials doing a variety of tasks [2-3]. This study does not focus on higher-level autonomy technologies, such as: autonomous management of on-board resources or opportunistic science. These are research topics in long-term system autonomy, but are outside the scope of the current study. Probabilities of hardware failure, landing and egress failures, or mission disabling events have not yet been included, but are currently under consideration.

A utility function describes the merit of completing different surface activities. The activities considered are long-range traverse, sample approach, and sample processing. Event tree analysis of these activities estimates likelihood of time delays due to technology failures and associated communication with Earth. The expected utility of the mission is computed by combining the utility of outcome with the probability of achieving the outcome. The analysis results in ranking of autonomy technologies. The ranking is based on technology development maximizing the expected utility of the mission.

2. Framework

The analytic framework comes from decision theory [1]. Our approach maximizes the expected return on investment subject to cost and schedule constraints. A network shown in figure 1 is created that models the influence of investments to technologies, to mission risk, and to science return.

3. Utility of outcomes

A mission can have many possible outcomes. The relative preferences of these outcomes are quantitatively described by a utility function subjectively asserted by the decision maker.

A utility function is defined over the set of possible outcomes. Results based on the utility function described in this section will be presented in later sections.

The utility function solicited from the MSL program is shown in figure 2 [5]. It is defined over the set of sequences of activities. This utility function suggests that 40% of the mission science return from processing samples will be obtained from the first sample processed through the analytic lab, with samples 2 and 3 contributing an additional 15% and samples 4 and 5 an additional 10%, respectively. The other metrics, range reached and samples measured with contact sensor, also have a decreasing marginal utility for larger values.

This utility function limits the possible outcomes to a set of specific sequences of completed activities. Implicitly, all other outcome sequences not in this set are excluded from possibility.

Now that the utility of the outcomes is at hand, it is necessary to estimate the probability of these outcomes.

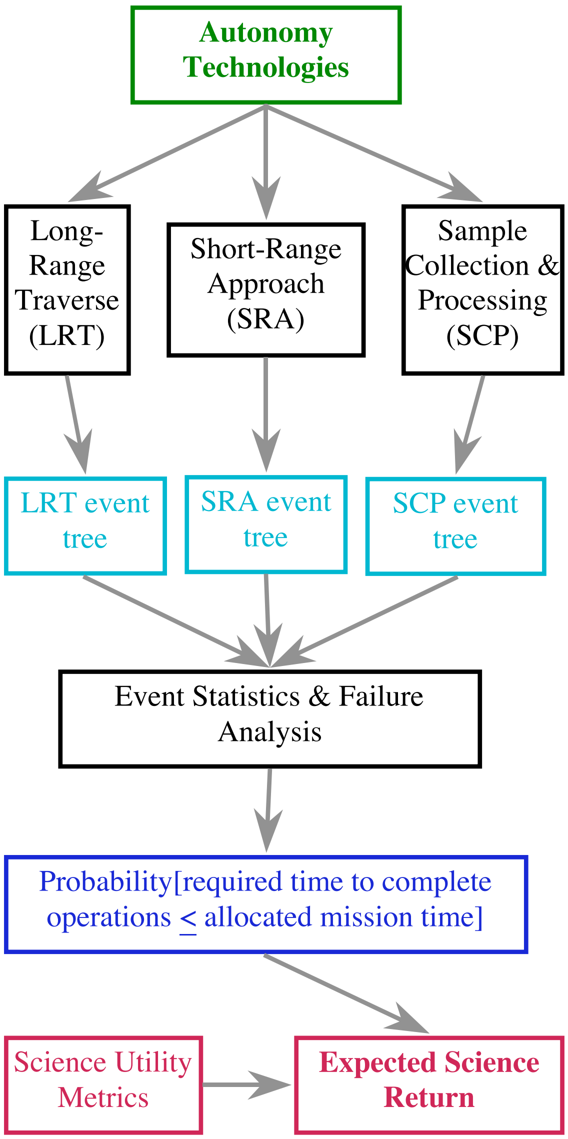

Figure 1. Block diagram of inference network. Autonomy technology developments influence the performance of surface activities. Event tree analysis estimates distributions of time needed to perform these activities. Utility metrics are combined with the probability estimates to give the expected science return.

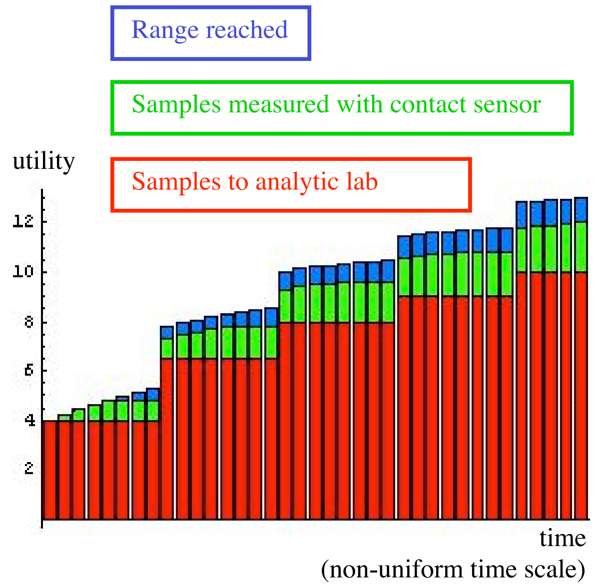

Figure 2. Utility function as a function of activities completed. The sequence in which activities are executed is 1) one sample processed by the analytic lab, 2) four contact sensor measurements obtained, and 3) traversal of 3 km to next science site The relative utility weighting for these operations is 10:2:1. The x-axis is increasing time as the activities are completed. The lowest portion of each bar represents the cumulative utility from samples processed by the analytic lab. The middle and highest segments represent the cumulative utility from contact sensor measurements and from the range reached respectively.

4. Probability of outcomes

The first step in estimating the probability of outcomes is to develop a flowchart of the sequence of steps for each of the activities performed during rover surface operations. There are three dominant activities: long-range traverse, approach activity, sample processing.

Figure 3 shows the flowchart for long-range traverse. Figure 4 shows the flowchart for the approach activity. Figure 5 shows the flowchart for the sample processing activity. The frequency of performing each step is calculated from the flowchart.

According to current plans, the SPAD (Sample Prep and Distribution System) will have a high degree of automation (fixed sequences of steps), but there is currently no perceived science autonomy within the SPAD. Consequently, the science processing checkpoints in the SPAD will continue to be supervised from Earth, rather than supervised by an autonomous science software agent. Time requirements for sample analysis are therefore dominated by the science processing checkpoints and the corresponding telecomm to Earth.

An event tree of each activity is derived from its flowchart. An event tree is a representation of all the events that can occur in the system. The events considered are the success or failure in performing each step. Each step in the flowchart has a number of failure modes. The failure modes considered in this analysis were failures that can be mitigated by autonomy technology development. The result of a failure is a delay of one or more communication cycles to diagnose and command the rover from Earth.

Failure modes and their failure rates are provided from JPL technology rover FIDO over the course of four years of field trials doing a variety of tasks [2,3]. The FIDO field trials were Silverlake, CA in April-May 1999, Black Rock Summit, NV in April 2000, Soda Mountains, CA in May 2001, and Gray Mountain, AZ in September 2002. All trials were run for ten days, and the Soda Mountains and Gray Mountain trials were done under flight relevant mission timelines and constraints in order to train the MER scientists.

A database is created that contains a row for each failure mode. The failure modes included are:

- Sparse range map
- No valid path plans
- Wheel wedge
- Drive step
- Localization
- False reference target(s)
- Science target out of FOV
- Workspace
- Hit arm
- Arm targeting

Tables 1-3 show the database for the three activities. The technology development estimate column gives a point estimate of the difficulty of the technology development to reduce the failure rate to zero. We currently are generalizing this estimate to account for a range of cost to performance relationships.

The event tree is used to estimate the probability distribution of the time necessary to complete each activity. From these estimates the probability of completing a sequence of activities within the mission time is computed. Figure 6 shows the probability distribution for the sequence of activities that the utility function was defined over. The probability distribution is based on no further technology development over that demonstrated in the FIDO field trials. Note that this distribution shown in figure 6 is a conditional distribution. It is conditioned on no mechanical or mission failures.

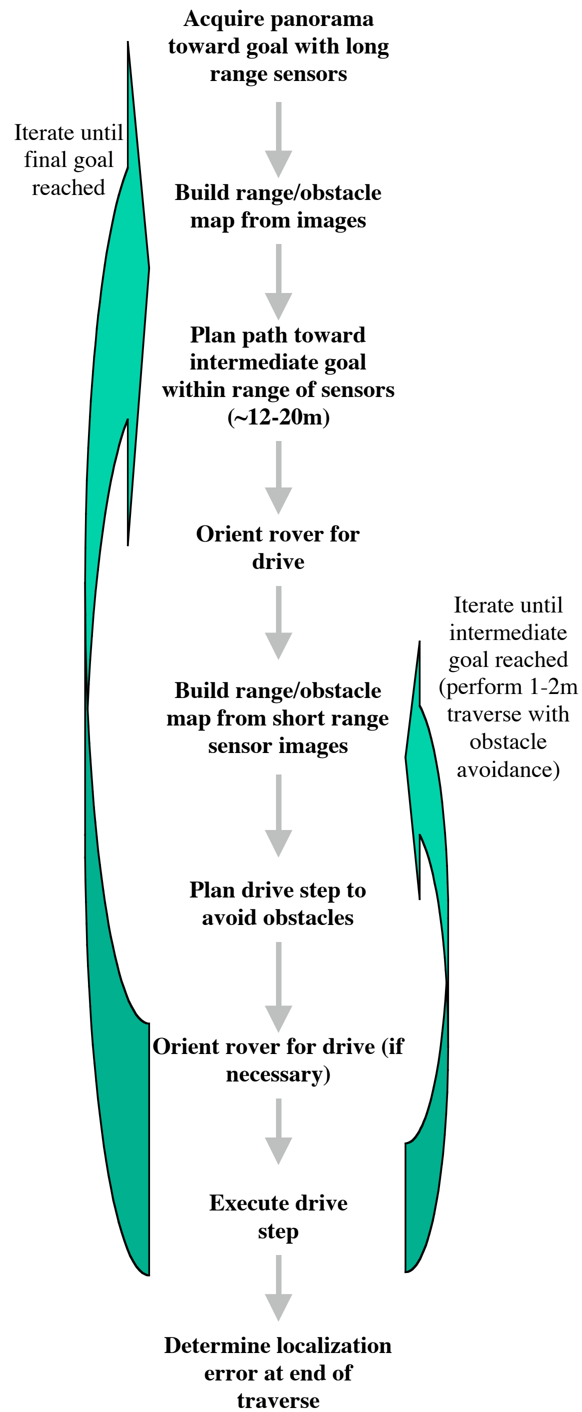

Figure 3. Flowchart of long-range traverse activity. The activity starts from the top of the

flowchart. Arrows show the sequencing of the steps.

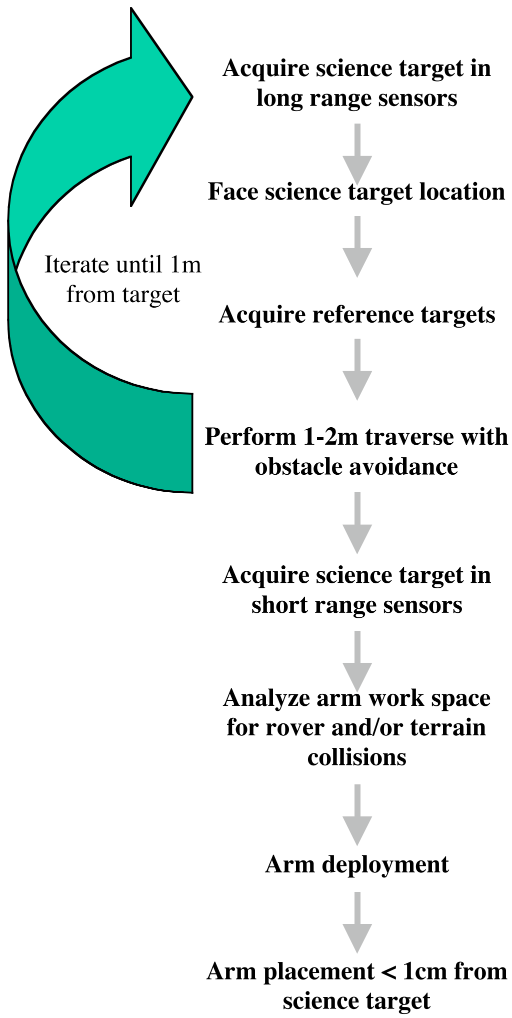

Figure 4. Flowchart of approach activity.

5. Objective function: Expected utility

Expected utility is the combination of the utility of the possible outcomes combined with the probability of the outcomes. This is described by equation 1.

$$\textit{Expected utility} = \sum_{outcome} u_{outcome}\, p_{outcome} \qquad (1)$$

where $\boldsymbol{u}$ is the utility function defined over the possible outcomes and $\boldsymbol{p}$ is the probability density function defined over these outcomes.

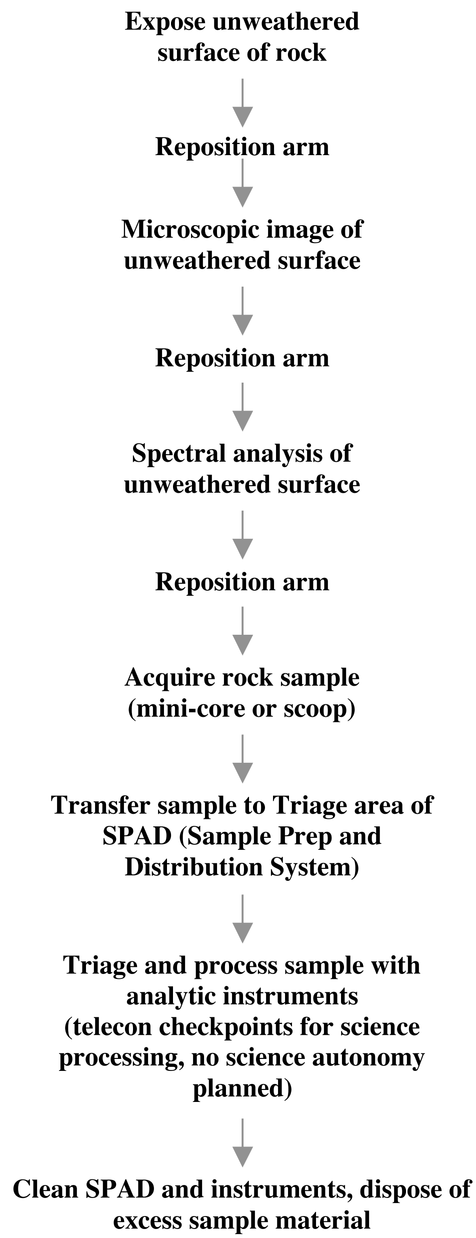

Figure 5. Flowchart of sample processing.

Table 1. Long-range traverse failure modes.

Failure mode	Failure rate	Freq. of step	Delay (sols)	Tech. Dev. Est.	Tech.
Range map	3/2500	Once per 1-2m	2	4	Camera models
Drive step	3/2500	Once per 1-2m	2	6-7	Short range path planning
Mosaic range map	1/20000 (derived estimate)	Once per 12-20m	2	4	Camera models
Path plan	1/250	Once per 12-20m	1	8-9	Long range path planning
Wheel wedge	1/1000	5 per 12-20m	2	7	Wheel wedge recovery
Local-ization	7/100-8/100	Once per 450m	2	4	Local-ization

Table 2. Sample processing failure modes.

Failure mode	Failure rate	Freq. of step	Delay (sols)	Tech Dev. Est.	Tech.
Repos-ition arm	1/1000	3 per anal-ysis	2	3-4	3D models
Acquire rock sample	1/10 (rough estimate)	Once per anal-ysis	2	5	Mini-coring
Transfer sample to Triage area	1/100	Once per anal-ysis	2	3-4	3D models

6. Constraint: Investment budget

Investment in autonomy technologies has the potential to reduce the failure rates associated with the failure modes. This in turn will influence the probability distribution in figure 6. Initially, we use estimates of technology development difficulty as a surrogate for technology development cost estimates.

The probability distribution of the outcomes is estimated as a function of the investment allocation. The investment allocation is a vector of the investment levels for each autonomy technology. The investment allocation must meet a budget constraint.

Table 3. Approach failure modes.

Failure mode	Failure rate	Freq. of step	Delay (sols)	Tech Dev. Est.	Tech.
Range map	2/100-51/100 (derived estimate)	Once per sample	2	4	Camera models
Drive step	2/100-51/100 (derived estimate)	Once per sample	3	6-7	Short range path planning
False ref. target(s)	2/100	Once per 1-2m	2	4	Track multiple relative features
Wheel wedge	1/1000	5 per sample	2	7	Wheel wedge recovery
Science target out of FOV	1/30	Once per sample	2	4	Relative position-ing
Work-space	3/300	Once per sample	2	3-4	3D models
Hit arm	1/300	Once per sample	2	3-4	3D models
Arm targeting	15/20	Once per sample	2	7	Target handoff to short range sensor

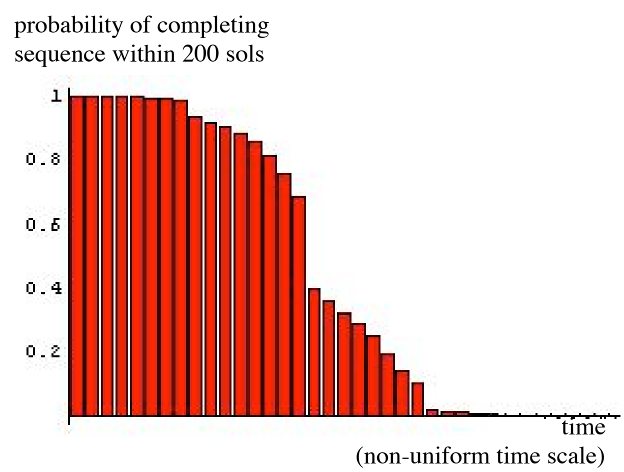

Figure 6. Probability of completing sequence of activities within a fixed mission time. The mission time of 200 sols is arbitrary. It was chosen to demonstrate the falloff in the probability of completing all the activities. The x-axis is increasing time as the activities are completed, and is the same as in figure 2.

The expected utility is now a function of the allocation and is given by equation 2.

$$Expected\ utility(Allocation) = \sum_{outcome} u_{outcome}\, p_{outcome}(Allocation) \qquad (2)$$

Our approach is to maximize expected utility subject to a budget constraint.

7. Ranking Results

The technologies considered can be ranked by a performance to cost ratio. Performance is defined by percent increase in expected utility.

A ranking of the technologies is shown in figure 7.

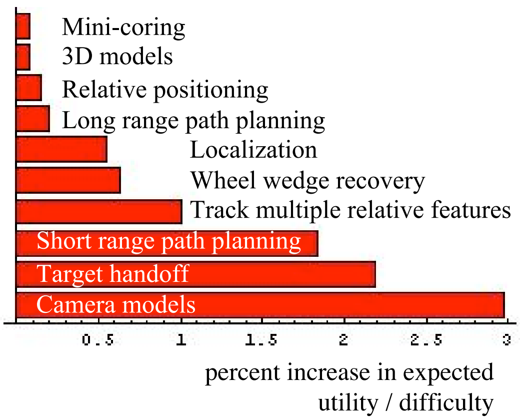

Figure 7. Ranking of autonomy technologies. The ratio of the marginal increase in expected utility to technology development difficulty is used to rank the technologies.

The analysis shows that autonomous calibration of camera models is an important technology because it impacts whether a wide range of autonomy functions can be done without ground-command intervention. Target handoff technology has a strong impact because it is needed for every sample approach and it mitigates a high failure rate. Autonomous short range path planning is also a significant technology because without it the amount of time required to complete surface operations grows to levels that severely degrade the expected utility of the mission.

The initial ranking is performed using point estimates of technology development difficulty. Based on the initial ranking, more detailed cost estimates are being solicited of the highest ranked technologies [4]. These refined estimates will include cost and performance uncertainties. This data also impacts the decision analysis since now the investment allocation depends on the absolute resources available, and not just the performance/cost ratio.

8. Conclusion

This work is useful in a number of ways. The first is to estimate achievable mission performance based on current estimates of failure rates. Next it can aid technology development decisions to obtain the best performance to cost benefit. Finally it can help design field tests specifically to provide relevant evidence about the most sensitive parameters.

Future work will include sensitivity analysis, generalization of the ranking procedure using cost and performance uncertainties, and enhancement of the computational framework.

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